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# IMPROVED NON LOCAL MEANS METHOD FOR SONAR IMAGE DENOISING

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**Abstract:** Due to poor visibility conditions, the underwater rich in abundant resource is still not well explored. The imaging technique is one of the methods to reveal the hidden treasure to the world. For this purpose optical imaging technique is used. Optical images suffer from poor visibility condition due to limited range of light and attenuation. So SONAR images based on acoustic or "Echo Sounding" principle, which suffers less attenuation, is used for exploring the underwater. Sonar photos are laid low with spatially varying clutters. Moreover there's a robust ardor in knowing what lies in underwater, So Side Scan SONAR device is used in underwater to capture the sea ground which hides maximum of the treasure. Sonar images play a critical position in oil exploration, mine's detection navigation, seabed mapping, fishing, ocean drilling, and etc. Therefore it will become a difficult challenge to captured sonar images that are susceptible to speckle noises, ambient noises, and so on. To dispose of noise from the picture without affecting the high-quality edges and edge maintaining filters need to be applied. So that a variety of methods have been introduced to remove noise from sonar images. However, many algorithms remove the fine details and structure of the image. Over the years a variety of methods have been introduced to remove noise from sonar images, such as Gaussian filtering, anisotropic filtering, and Total Variation minimization. However, many of these algorithms remove the fine details and structure of the image in addition to the noise because of assumptions made about the frequency content of the image. The non-local means algorithm does not make these assumptions, but instead assumes that the image contains an extensive amount of redundancy. These redundancies can then be exploited to remove the noise in the image. This project will implement the non-local means algorithm and compare it to other denoising methods using the method noise measurement. The main focus of this work is to propose an improved non-local means algorithm addressing the preservation of structure in a sonar image.

**Keywords:** Side Scan Sonar imaging, Non Local Means, Method Noise, Poisson Noise.

## 1.0 Introduction

Sonar statistics are commonly offered as gray level photographs [1]. However, Sonar photos often show putting variations in brightness. These variations, resulting from the sonar beam sample and the constantly changing mindset make the photos difficult to read as photos of the seabed. This reduces the utility of the photographs for marine geologists. The Sonar is a powerful, versatile but low value tool for surveying the sea ground. Usually a deliver tows a tow fish [2] hooked up with sonar arrays, one on each side. The Sonar arrays emit fan-shaped sonar indicators perpendicular to the course of travel. The signals scan a swath of sea ground from a factor just under the tow fish to a restrained distance away from the road of travel on both aspects. The raw sonar data are time collection of digitized sound: the lower back-scattered indicators from each ping on the port and starboard sides of the tow fish. If we display the records as grey degree pixels representing the acoustic power, the result is a photograph much like the left facet of Fig. 1.1. This is also called a waterfall display.

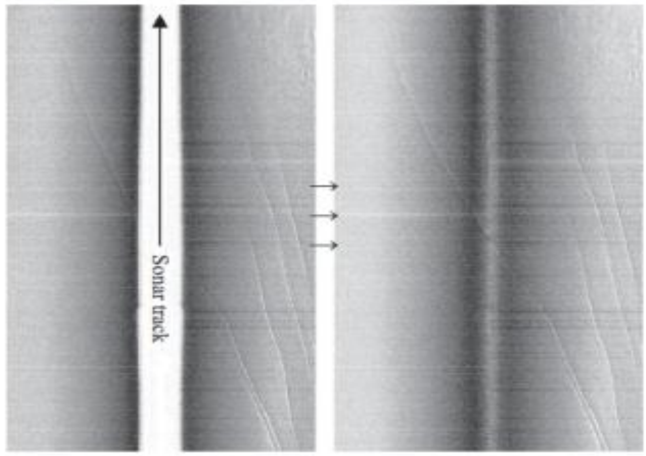


Fig. 1.1: Sonar data before and after slant range correction [3]

Images primarily based at once on the raw time collection facts have a blind zone inside the middle, so for most functions, we do no longer use the statistics in this uncooked form. The uncooked waterfall wishes to be processed into an photograph which kind of corresponds to a plane place of the ocean ground. The most basic shape of processing for Sonar statistics is "slant variety correction". For this technique, we expect that the seabed is a great flat plane. Then, given the altitude of the tow fish, and the time at which the backscatter reaches the sonar array, we are able to calculate a function on the seabed. After processing the facts, the blind area inside the center of photo disappears, and every datum is relocated to a function greater consultant of the actual seabed. Figure 1.1 suggests an example of a waterfall photo before and after slant range correction. The scan range for each side is about 400 m. The terrain features shown are several elongated small normal faults on a slope of sea bottom [4] .
The solid curves represent the relative intensity of sonar emission in different directions. The horizontal axis denotes the grazing perspective; the vertical axis denotes the relative intensity.

All the pix on this paper have been processed primarily based on 16-bit uncooked intensity information, where the darker grey shade manner higher depth of backscattering. In popular, the 16-bit raw records allows more bendy assessment exaggeration processing than the 8-bit statistics set. Most images on this paper were more suitable in gray level contrast to some extent with none facet impact of coloration discontinuity. If the case become eight-bit, many shade discontinuity or terrible satisfactory in the images would be inevitable.

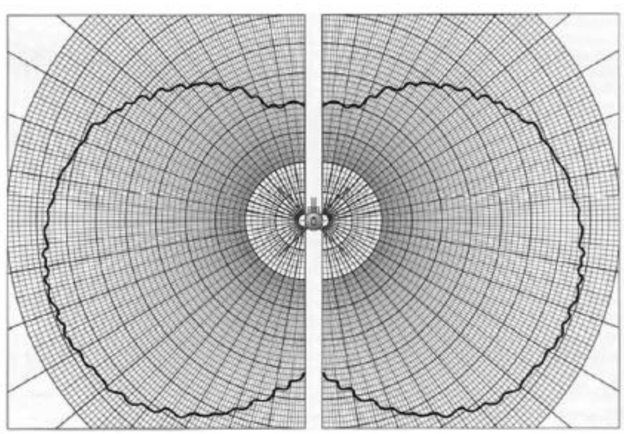

Fig.1.2: A typical beam pattern for Sonar equipment [5]

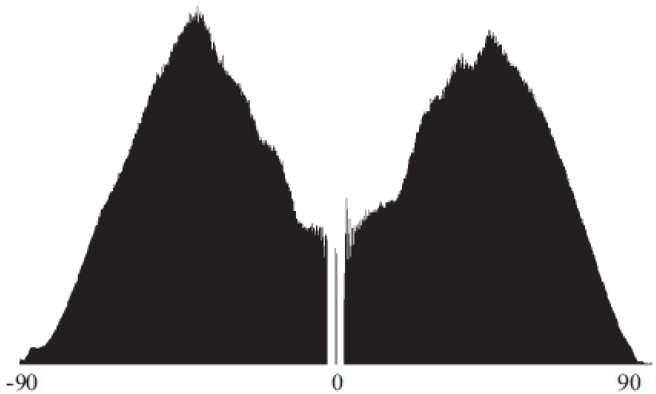


*Fig.1.3: Back-scattered energy as a function of grazing angle [6]*

## 2.0 Noise Reduction

Noise discount is the technique of disposing of noise from a sign[7] . All recording gadgets, each analog and digital, have trends that lead them to prone to noise. Noise may be random or white noise with no coherence, or coherent noise delivered by using the tool's mechanism or processing algorithms. In electronic recording gadgets, a prime form of noise is hiss resulting from random electrons that, heavily inspired by way of warmness, stray from their particular route. These stray electrons have an impact on the voltage of the output signal and therefore create detectable noise.

In the case of photographic film and magnetic tape, noise (each visible and audible) is added due to the grain structure of the medium. In photographic film, the size of the grains in the movie determines the film's sensitivity, more touchy film having larger sized grains. In magnetic tape, the bigger the grains of the magnetic particles (generally ferric oxide or magnetite), the extra inclined the medium is to noise. To catch up on this, larger areas of movie or magnetic tape can be used to decrease the noise to a suitable degree [8]. Many noise discount algorithms tend to damage more or much less alerts. The neighborhood sign-and-noise orthogonalization set of rules [9] can be used to avoid the damages to alerts. A sort of strategies had been introduced to take away noise from sonar snap shots. However, many algorithms cast off the great information and structure of the photo in addition to the noise because of assumptions made about the frequency content of the photo. Basic processes for denoising, consisting of Gaussian and median filtering, will be predisposed to over-clean edges and do away with image element. More sophisticated strategies use the properties of natural photo facts to enhance massive depth edges and suppress lower intensity edges. This assets has been utilized by wavelet techniques, anisotropic diffusion, bilateral filtering, and Field of Experts fashions. The non-neighborhood method (NL-manner) photograph denoising algorithm is introduced based totally on weighted averaging and similarity of patches. In addition to conventional, direct assessment, discount of computational fee using primary aspect analysis (PCA) has been employed with promising end result. Over the years a ramification of methods were brought to remove noise from sonar pix, along with Gaussian filtering, anisotropic filtering, and Total Variation minimization. However, many of those algorithms get rid of the first-rate information and structure of the photo similarly to the noise due to assumptions made approximately the frequency content material of the image. The non-nearby means set of rules does now not make those assumptions, but as an alternative assumes that the image includes an in depth amount of redundancy. These redundancies can then be exploited to remove the noise within the picture. This venture will put into effect the non-neighborhood method set of rules and compare it to different denoising methods using the method noise dimension. The non-nearby means set of rules does no longer make those assumptions, however rather assumes that the photograph contains an intensive amount of redundancy.

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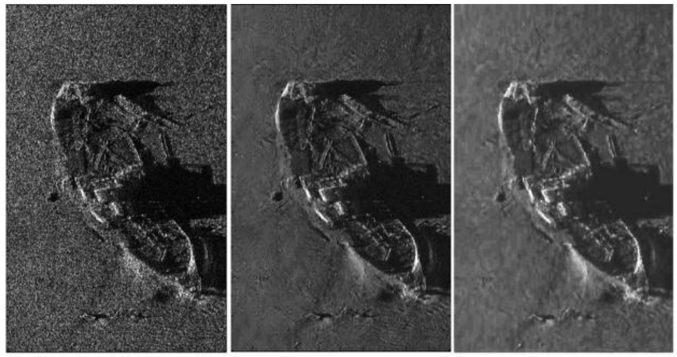

*(a)* *(b)* *(c)*

Fig. 2.1 (a) First image is with noise, (b) middle image is original image and (c) the rightmost image is the restored image [10]

Here, the leftmost image is the original image, the middle image is imposed with noise, and the rightmost image is the restored image using the 4th order model. Another approach is to combine a 2nd and 4th order method. The idea here is that smooth regions are filtered by the 4th order scheme, while edges are filtered by a 2nd order scheme. To choose in which areas of the image each of the models are to be used, one has to construct a weight function. Another way of denoising images is the following: Instead of working directly with the images, the noisy normal vectors of the image are processed instead. Then, the smoothed normal vectors are used to reconstruct a denoised image.

## 3.0 Related Works

**Tan j., et. al. (2015)** worked on the compressive imaging troubles, where photographs are reconstructed from a reduced quantity of linear measurements. The goal is to improve over existing compressive imaging algorithms in terms of each reconstruction error and runtime. To pursue our objective, we advocate compressive imaging algorithms that appoint the approximate message passing (AMP) framework. AMP is an iterative sign reconstruction algorithm that performs scalar denoising at each generation; so as for AMP to reconstruct the original input sign well, a terrific denoiser must be used. We apply wavelet-based totally photo denoiser inside AMP. The first denoiser is the "amplitude-scale-invariant Bays estimator" (ABE), and the second is an adaptive Wiener filter; we call our AMP-primarily based algorithms for compressive imaging AMP-ABE and AMP-Wiener. Numerical results display that both AMP-ABE and AMP-Wiener considerably improve over the country of the art in terms of runtime. In terms of reconstruction fine, AMP-Wiener offers decrease suggest-rectangular error (MSE) than present compressive imaging algorithms. In comparison, AMP-ABE has better MSE, due to the fact ABE does now not denoiser in addition to the adaptive Wiener filter out [11]. Therefore **Zhao Y.Q., et. al. (2015)** worked on Hyper spectral picture (HSI) denoising is an vital preprocess step to improve the overall performance of subsequent applications. For HSI, there's lots international and nearby redundancy and correlation (RAC) in spatial/spectral dimensions. In addition, denoising overall performance may be advanced greatly if RAC is utilized correctly within the denoising process. In this paper, an HSI denoising method is proposed via collectively utilizing the global and local RAC in spatial/spectral domain names. First, sparse coding is exploited to version the global RAC inside the spatial area and neighborhood RAC within the spectral domain. Noise can be eliminated by sparse approximated information with learned dictionary. At this level, simplest neighborhood RAC within the spectral area is hired. It will reason spectral distortion. To compensate the lack of neighborhood spectral RAC, low-rank constraint is used to deal with the worldwide RAC within the spectral domain. Different hyper spectral data units are used to check the performance of the proposed approach. The denoising effects by the proposed technique are superior to results obtained by using other latest hyper spectral denoising strategies [12]. After that **Cheng W., et. al. (2015)** presented a pixel values of pictures taken with the aid of an image sensor are said to be corrupted with the aid of Poisson noise. To date, multiscale Poisson photo denoising strategies have processed Haar frame and wavelet coefficients-the modeling of coefficients is enabled by means of the Skellam distribution evaluation. We increase those results by fixing for shrinkage operators for Skellam that minimizes the danger purposeful within the multiscale Poisson photograph denoising placing. The minimum threat shrinkage operator of this kind efficiently produces denoised wavelet coefficients with minimum manageable L2 errors [13].Therefore **Censor W., et. al. (2016)** took the implicit convex feasibility hassle attempts to find a factor in the intersection of a finite family of convex sets, some of which aren't explicitly decided however may additionally vary. We expand simultaneous and sequential projection strategies capable of dealing with such problems and display their applicability to picture denoising in a selected medical imaging state of affairs. By allowing the variable units to go through scaling, transferring and rotation, this paintings generalizes preceding consequences wherein the implicit convex feasibility trouble became used for cooperative wi-fi sensor community positioning in which units are balls and their centers had been implicit [14]. After that **Hassani A., et. al. (2016)** [15] The green Non-Local Means denoising set of rules modifies the depth of each pixel by way of the weighted common of all comparable pixels within the noisy photo. It stems from the assumption that there are many comparable systems in sonar pix. Many adaptations of the NLM filter out has been broadly used for MRI picture denoising. The Unbiased NLM is a popular this type of techniques which subtracts the Rican noise bias from the NLM filtered image. The bias can be expected from the MRI picture background. Prior to that, the heritage wishes to be extracted from the photo. However, the envisioned Rican noise bias depends strongly at the segmentation technique which influences the set of rules overall performance The obtained historical past is used to estimate the noise bias while the Unbiased NLM filter is implemented topically at the received foreground the use of the estimated bias. Experimental effects show that the proposed method perform better than the NLM clear out and the UNLM underneath all examined noise tiers [15]. After that **Jain S. K., et. al. (2016)** They deals with an anisotropic diffusion primarily based noise elimination approach which makes use of the new diffusion characteristic primarily based on tangent sigmoid function. A local part indicator feature based totally on local shape tensor is likewise used in the proposed method, to reduce the noise and detection of edges in virtual pix. From the experimental effects, we look at that the proposed approach is better and close to to the alternative cutting-edge methods, in phrases of both qualitatively and quantitatively. Numerical checks had been performed on diverse photographs, which can be corrupted by using Gaussian noise and consequences illustrate that the proposed method is greater green than current one [16].Therefore **Xiaoming L., et. al. (2017)** worked on image denoising is a essential step earlier than acting segmentation or function extraction on an photograph, which influences the very last bring about photograph processing. In recent years, utilizing the self-similarity traits of the pics, many patch-primarily based picture denoising strategies have been proposed, but most of them, named the internal denoising techniques, utilized the noisy photograph only where the performances are restrained by means of the constrained facts they used. We proposed a patch-based totally technique, which uses a low-rank method and targeted database, to denoised the optical coherence tomography (OCT) photograph. When choosing the similar patches for the noisy patch, our technique mixed inner and outside denoising, utilizing the alternative photographs applicable to the noisy picture, in which our centered database is made up of those varieties of photographs and is an development compared with the previous techniques. Next, we leverage the low-rank method to denoised the group matrix which include the noisy patch and the corresponding similar patches, for the reality that a easy photograph may be visible as a low-rank matrix and rank of the noisy picture is a lot large than the smooth photo. After the first-step denoising is completed, we take advantage of Gabor remodel, which taken into consideration the layer characteristic of the OCT retinal photographs, to construct a loud image earlier than the second step. Experimental results display that our method compares favorably with the prevailing brand new techniques [17]. After that **Ahn B., et. al, (2017)** worked on the image denoising is a crucial step earlier than appearing segmentation or feature extraction on an image, which affects the final result in photograph processing. In current years, making use of the self-similarity traits of the photographs, many patch-based totally image denoising techniques were proposed, but maximum of them, named the internal denoising strategies, utilized the noisy photo handiest where the performances are restricted via the limited facts they used. We proposed a patch-primarily based technique, which uses a low-rank approach and targeted database, to denoised the optical coherence tomography (OCT) photo. When selecting the same patches for the noisy patch, our approach mixed internal and outside denoising, utilizing the alternative pix applicable to the noisy photo, wherein our centered database is made up of those types of images and is an development compared with the preceding strategies. Next, the low-rank approach to denoised the organization matrix along with the noisy patch and the corresponding comparable patches, for the fact that a smooth picture may be seen as a low-rank matrix and rank of the noisy photograph is a good deal larger than the clean image. After the first-step denoising is performed, we take advantage of Gabor transform, which considered the layer feature of the OCT retinal pictures, to assemble a loud picture earlier than the second one step. Experimental results display that our technique compares favorably with the present today's techniques. Non-local means is an algorithm in image processing for image denoising. Unlike "local mean" filters, which take the mean value of a group of pixels surrounding a target pixel to smooth the image, non-local means filtering takes a mean of all pixels in the image, weighted by how similar these pixels are to the target pixel. Recently non-local means has been extended to other image processing applications such as deinterlacing and view interpolation [18].

## 4.0 Non-Local Means Method

Each pixel *p* of the non-local means denoised image is computed with the following formula:

$$NL(V)(p)=\sum_{q\in V} w(p,q)V(q) \qquad (1)$$

where *V* is the noisy image, and weights *w(p,q)* meet the following conditions $0\leq w(p,q)\leq 1$ and $\sum_q w(p,q)=1$ Each pixel is a weighted average of all of the pixels within the image. The weights are based at the similarity between the neighborhoods of pixels p and q. For instance, in Figure1 above the burden w(p,q1) is a great deal extra than w(p,q2) because pixels p and q1 have comparable neighborhoods and pixels p and q2 do no longer have comparable neighborhoods. In order to compute the similarity, a neighborhood need to be defined. Let Ni be the square community targeted about pixel i with a person-defined radius Rsim. To compute the similarity between two neighborhoods take the weighted sum of squares distinction among the 2 neighborhoods or as a formula $d(p,q)=\|V(N_p)-V(N_q)\|^2_{2,F}$. *F* is the neighborhood filter applied to the squared difference of the neighborhoods and will be further discussed later in this section. The weights can then be computed using the following formula:

$$w(p,q)=\frac{1}{Z(p)}e^{\frac{-d(p,q)}{h}}$$

*Z(p)* is the normalizing constant defined as $Z(p)=\sum_q e^{\frac{-d(p,q)}{h}}$. *h* is the weight-decay control parameter.

## 5.0 Result Analysis & Observations

A method for an intelligent handover decision mechanism among different radio access networks where the available network set is obtained dynamically at the mobile client comprises. This is because the burden w(p, p) may be tons greater than the weights from every other pixel inside the picture. By definition this makes sense due to the fact every community is much like itself. To save you pixel p from over-weighing itself let w (p, p) be same to the most weight of the alternative pixels, or in greater mathematical terms $w(p,p)=max\{w(p,q)\mid p\neq q\}$


**Fig 5.1: Noisy image with Poisson Noise**

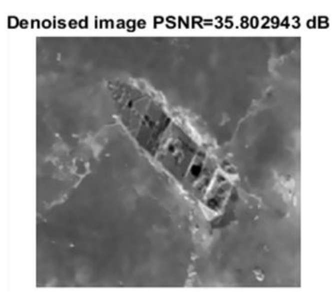


***Fig.5.2: NL Filtered Image at Poisson Noise (σ=15)***

**TABLE 5.1 Comparison of various image at Poisson Noise (σ=25)**

| Sr. No. | Image | Noise Image | Normal Method | Base paper | NL Proposed |
|---|---|---|---|---|---|
| 1. | Sonar 1 | 22.2 | 26.05 | 26.7 | 31.34 |
| 2. | Sonar 2 | 22.17 | 29.9 | 30.7 | 39.61 |
| 3. | Sonar 3 | 22.13 | 25.95 | 26 | 39.64 |
| 4. | Sonar 4 | 22.07 | 29.85 | 30.8 | 37.09 |
| 5. | Sonar 5 | 22.035 | 29.8 | 30.45 | 41.24 |
| 6. | Sonar 6 | 21.992 | 30.545 | 31.21 | 42.968 |

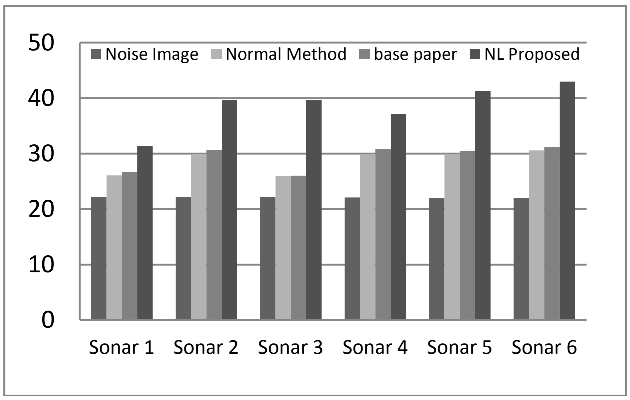


Fig. 5.3: Comparison of various image at Poisson Noise (σ=25)

**TABLE 5.2: Comparison of various images at Poisson Noise (σ=15)**

| **Sr** | **Image** | **Noise Image** | **Normal Method** | **Base Paper** | **NL-Proposed** |
|---|---|---|---|---|---|
| 1. | Bridge | 24.8 | 27.8 | 28.2 | 30.30 |
| 2. | Lena | 24.6 | 31.5 | 32.1 | 34.56 |
| 3. | Mandrill | 24.6 | 27.5 | 27.7 | 30.57 |
| 4. | Peppers | 24.6 | 31.4 | 32.2 | 35.33 |

## 6.0 Conclusion and Future Scope

Most pictures are subjected to degradation due to the presence of noise from numerous assets. For further processing of the pictures and for effective visible analysis, the noise need to be removed. Many denoising algorithms had been proposed for enhancing snap shots. Preserving the structural information has its very own significance in picture denoising, and specially for plenty sorts pix it must now not be compromised.

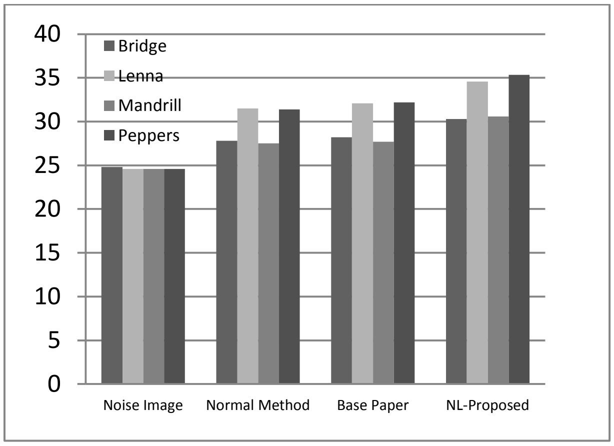


**Fig. 5.4: Comparison of various image at Poisson Noise (σ=15)**

For effective photo denoising, the records distribution within the pics need to be recognized in advance. Data in the magnitude pix are gaussian disbursed. Among the currently proposed denoising strategies for decreasing noise, non-nearby maximum chance estimation method (NLML) proved to be an efficient one. But the advanced overall performance of the NLML is constrained via its high computational complexity and non-finest way of selecting the samples for ML estimation. In this paintings we cope with the above issues to some enlarge by using introducing new NL method. The proposed method targets to reduce the computational complexity and improves PSNR overall performance. Comparative analysis of the proposed method with traditional NLML method based on the execution time and quantitative analysis in phrases of PSNR, SSIM, MSE and suggests that the proposed method has an aspect over the conventional approach.

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